Analysis And Detection of Monkeypox Using Machine Learning

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Submitted by

AKRISHT KUMAR

2K22/SWE/02

Under the supervision of

Mr. SANJAY PATIDAR

Assistant Professor
Department of Software Engineering

Department of Software Engineering
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi 110042

MAY, 2024

DEPARTMENT OF SOFTWARE ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

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Place: Delhi

Date: 22 May 2024

Akrisht Kumar

Roll No. 2K22/SWE/02
Department of Software Engineering
Delhi Technological University

DEPARTMENT OF SOTWARE ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)Bawana Road,
Delhi-110042

CANDIDATES' DECLARATION

I, Akrisht Kumar (2K22/SWE/02), student pursuing Master of Technology in Software Engineer-ing, hereby declare that my project, "Analysis And Detection of Monkeypox Using Machine Learning" in partial fulfilment of the requirement for being awarded the degree of Master of Technologyin Software Engineering submitted in the Department of Software Engineering, Delhi Techno-logical University is an authentic record of my work carried out during the period from January to May, 2024 under the supervision of Mr. Sanjay Patidar. I have cited all my references with proper credit.

This work has not erstwhile formed the foundation for the award of any Degree, Diploma Associateship, Fellowship or other similar title or any other recognition.

Candidate's Signature

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

Signature of Supervisor

DEPARTMENT OF SOFTWARE ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

CERTIFICATE

I certify that the Project Dissertation titled **Analysis And Detection of Monkeypox using Machine Learning** which is submitted by **Akrisht Kumar (Roll No. 2K22/SWE/02)**, Department of Software Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the Project Work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: Delhi

Date: 22 May 2024

Mr. Sanjay Patidar
Assistant Professor
Department of Software Engineering
Delhi Technological University

ABSTRACT

Monkeypox is an infectious disease with very important implications for public health. Therefore, it is not just the development of methods for detection that could be quickly carried out; they also must have enough accuracy to manage and control it effectively. This thesis carries out an elaborate kind of study on the use of deep learning techniques in the development and evaluation of computer software purposed for the detection of monkeypox. This will be done by developing and testing deep learning architectures for identifying monkeypox using skin lesion images, which can enable the quick and accurate detection of any case of monkeypox. We develop different deep learning architectures and strategies to optimize image processing techniques that extract meaningful data out of skin lesion images in our study.

Key performance metrics, like accuracy, sensitivity, and specificity, are given much emphasis in the assessment of the effectiveness of the models. This shows a very good recall for our deep learning models: EfficientNetB3 89.8%, VGG16 90.4%, and ResNet50 93.8%. By using the Monkeypox Skin Lesion Dataset 2.0 (MSLD 2.0) only, we remove all questions about reliability or validity in our results. This means that robust training and evaluation of the model can be performed. Our study helps to improve monkeypox detection systems, automate such processes for public health outcomes, and ensure the intervention accorded is timely in communities affected by the disease.

Those could be some great insights on the performance of deep learning models for monkeypox detection and how they underline matter-of-factly the strengths and weaknesses of different architectures. We clarify more on the role of deep learning by further rigorous experimentation and continuous analysis in aiming to enhance the accuracy and efficiency of the monkeypox detection system. We foster advancements in deep learning methodologies for infectious disease detection through focusing on collaborative research efforts, sharing knowledge across the scientific community, and translating into better health care at a global level.

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LIST OF ABBREVIATION

MPox	Monkeypox
MSLD	Monkeypox Skin Lesion Dataset
ML	Machine Learning
DL	Deep Learning
CNN	convolutional neural network

CHAPTER 1

INTRODUCTION

In recent years, the scenario of infectious diseases around the world is gradually reappearing with more than just an emerging threat underlining the urgent need for new and effective systems for the early diagnosis of diseases. Monkeypox is a rare zoonotic virus with public health repercussion potential; over decades, it has been receiving an increased attention due to its capability of causing outbreaks in human beings. Many of these traditional diagnoses are generally difficult, slow, and laborious. Thus, in view of all these pitfalls, the introduction of strict computational techniques for machine learning and deep learning has lately emerged as a probable way of improving precision and timeliness in the detection of monkeypox.

Therefore, this paper seeks to provide an in-depth review of the detection methodologies currently in use for monkeypox and will focus on the important, transformative role of ML and DL algorithms [1]. In this regard there can be no doubt that computational intelligence will play a revolutionizing role in the field of infectious disease diagnostics. Exploring ML and DL applications in monkeypox detection is not only timely but also indispensable to outpace our efforts in the current fight against newly emerging viral threats.

This review attempts to classicize the rich selection of ML and DL approaches that have been applied in the determination of monkeypox by an exhaustive look at valuable recent studies, experimental findings, and technological advances [2]. From image analysis and genomic sequencing to data interpretation on epidemiology, the incorporation of such state-of-the-art technologies gives the best insight into early prediction, classification, and identification of monkeypox cases. Also, the paper will get insight into the challenges and future prospects of applying ML and DL techniques in infectious disease surveillance, thereby guiding them on the pathway to a more resilient and responsive health sector.

The balance is shifting further towards the critically important integration between biological insight and computational power in our continued challenge to manage infectious diseases [1]. From this end, the review presented herein has been prepared not only to report on recent developments in ML and DL applications for monkeypox detection but also on efforts pushing for the enhancement of our preparedness against emerging infectious threats. [3]

1.1. Machine Learning

Machine learning is a subfield of artificial intelligence where algorithms provide predictions or make decisions based on data [2]. Techniques running the gamut from supervised learning—in which the algorithm learns from labeled data—to unsupervised learning—where the aim is to uncover underlying structure within unlabeled data—to reinforcement learning, in which the rules are learned by the algorithm through trial and error, can all be grouped under it [1].

1.2. Deep Learning

Deep learning is a subfield of machine learning dealing with the training of deep neural networks; it focuses on neural networks with many layers, which is to say very "deep" networks, in order to perform analyses on almost all kinds of information. [3] As a result, these deep neural networks automatically learn to discern subtle patterns and features within data, thus being very powerful for tasks such as image recognition and classification. [4]

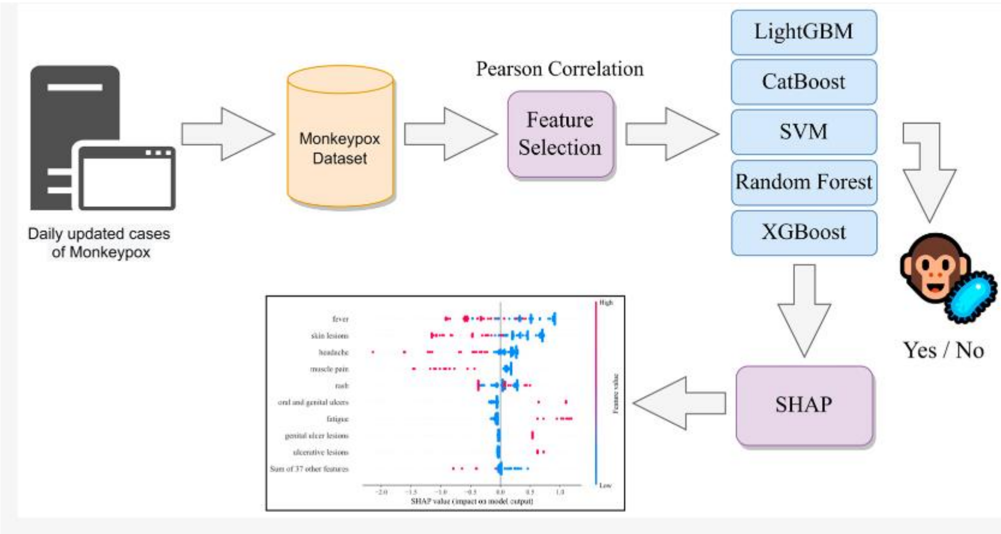

Fig.1: General Workflow for the detection of monkeypox using machine learning [5]

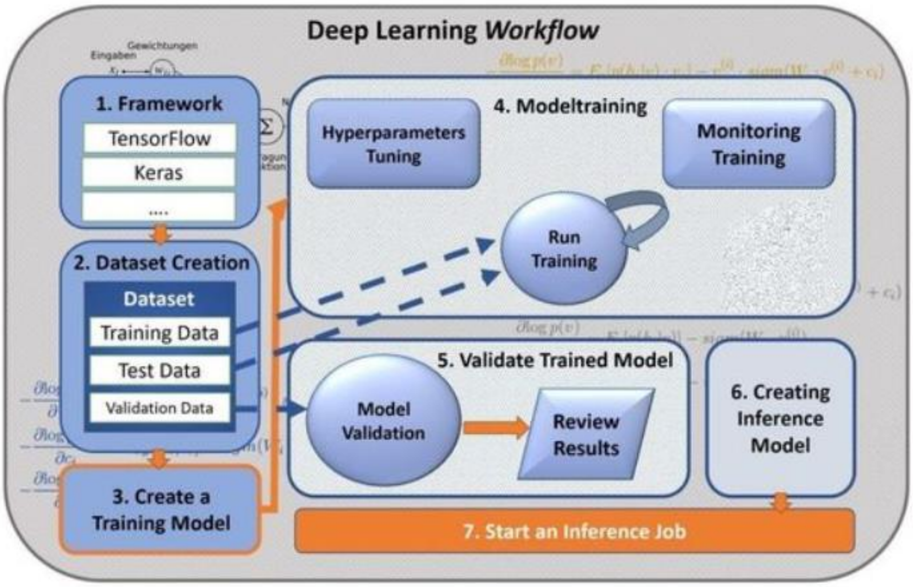

Fig.2: General workflow for the detection of monkeypox using deep learning [6]

1.3. Image Detection Using Deep Learning

Image detection is generally done using feature extraction and classification: machine learning techniques. For instance, in traditional ML algorithms like SVM and random forests, image features have to be manually extracted by a domain expert who identifies which features of an image are most relevant for the particular case of classification. Those features may potentially be edges, textures, or some specific images.
On the other hand, deep learning automates feature extraction. [7] Currently, convolutional neural networks are the most famous deep learning architecture used for image tasks since they learn hierarchical representations of the data. In CNNs, early layers can detect simple features such as edges or textures, while deeper layers are good at detecting complex structures like shapes or whole objects. This capability of learning the features automatically becomes an advantage for deep learning in object detection.

The decision between machine learning and deep learning will depend on a number of factors including: Deep learning techniques generally require a large amount of data to run, since they learn feature representations directly from the data. Prediction model techniques like CNN will thus most likely outperform traditional machine learning methods because of the availability of large labeled datasets. Otherwise, for small datasets, classic machine learning techniques probably do a better job, unless techniques like data augmentation or transfer learning are applied. Computational Resource Requirement: Deep learning models are computationally expensive in the required use of very high computational resources during training. In most cases, traditional machine learning methods do not need the same amount of computational power. For tasks that are defined as complex and, accordingly, include high-dimensional data such as images, videos, and audio, deep learning models are typically much more effective because of their entangling capability in capturing intricate patterns and dependencies. [8] For easier tasks or tasks whose features are well defined, traditional machine learning methods may suffice, being usually more efficient in these cases. Often, interpretability matters for the use case of the application, and traditional machine learning models are said to be more interpretable compared to deep learning models. In such situations, transparency and interpretability of the model would be a concern, and one might prefer simpler models in machine learning.

This focuses on deep learning techniques in the detection of monkeypox from images of skin lesions. Since this is available within Monkeypox Skin Lesion Dataset 2.0 [9] and entailing the task's complexity, models from deep learning, especially from within convolutional neural networks, by far present the best alternative. The models are trained to automatically learn relevant features from presented images that will be effective in boosting accuracy and efficiency in the process of detection.

CHAPTER 2

LITERATURE REVIEW

This chapter presents the literature review, a critical section of this thesis, and it provides an exhaustive overview of past research and studies associated with the analysis and detection of monkeypox using artificial intelligence and deep learning methodologies. In this part of the paper, knowledge of the diagnosis of monkeypox, as well as the methods, approaches, and results obtained in previous researches, are presented. In combining and analyzing this information, we intend to set a strong base for our research and also contribute to the further discourse in the field.

The role of the literature review is to frame a research question guiding the study and to make explicit the central inquiry that motivates our work.

We have outlined various research studies and made a review of major research works on detecting monkeypox. Each and every study is reviewed closely and elaborated in terms of the methods used, data, and results. This will enable us to provide a comprehensive look at the strength, weaknesses, and gaps in the existing literature.

As we travel through the existing literature, there appears to be places where a gap in knowledge exists or further inquiry is needed. These are nothing but the knowledge gaps that identify our research gap; that is, the specific areas where our study targets valuable additions. In other words, we may pinpoint and throw light on the research gaps, thereby underlining the importance and relevance of our own investigation in the larger context of scholarly inquiry. The literature review ended with a statement regarding the research objective of this study. In detail, it shows what is to be found out regarding the aim and objectives of our study. This essentially defines the purpose and coverage of our intended research work and thus brings clarity on the projected outcome and contribution of the thesis.

The literature review, however, will only provide a sketch of the synthesized relevant information by existing literature, since the ways through which it guides the reader to the rationale, methodology, and findings of the present study focusing on monkeypox detection using machine learning and deep learning techniques.

The aim of this study is to apply deep learning models for the detection of skin lesions caused by monkeypox. Researchers have tried different models, including MobileNetV2, VGG16, and VGG19, on datasets of monkeypox skin images. It is achieved that the MobileNetV2 model detects best with an accuracy of 91.38%, together with respectable recall, precision, and F1 score. In this paper, we emphasize how deep learning methods would help in the diagnosis of monkeypox, especially when PCR testing is not available.

[11] Transfer learning for skin lesion classification in monkeypox: The goal of this paper is to classify between the different classes of skin lesions that appear due to monkeypox using transfer learning. Skin lesion images were collected and then trained by the use of five different ConvNets—Xception, ResNet 50, Inception v3, MobileNetv2, and EfficientNetB5—to classify skin lesion photos that appear as a result of monkeypox. From all these, it is found out that MobileNetv2, with an accuracy of 98.78%, was more correct in classifying photos of skin lesions caused by monkeypox. This study demonstrates that deep and transfer learning techniques have the potential to automate the identification of skin lesions in association with monkeypox cases when PCR testing is not readily available.

This paper reaffirms and introduces a machine learning algorithm for the diagnosis of the monkeypox-sick based on RGB photographs. The authors applied six machine-learning classifiers and three convolutional neural network modes on an open dataset. The research had seen the application of pre-trained CNN features of some MLCs with various effectiveness and so could propose a better slope-fusion-based method for enhanced diagnosis accuracy. In areas where confirmatory PCR tests are not available within a short period, this study highlights the relevance of machine learning techniques in early detection and surveillance of monkeypox.

As such, the study in [13] puts forward models for the detection of monkeypox skin disease with the use of deep learning using its five pre-trained models: namely, DesNet121, ResNet50, Xception,

The monkeypox image dataset was experimented using EfficientNetB3 and EfficientNetB7 over Kaggle, with detection accuracy ranging variably between 72% and 90%. In this connection, it could be said that deep learning models can help a physician in screening and detecting monkeypox at an early stage.

Another recent study [14] researched the analysis and detection of monkeypox using the GoogLeNet model. Four basic deep learning pre-trained models used in this classification of illnesses due to monkeypox include VGG-16, ResNet50, InceptionV3, and GoogLeNet. The overall accuracy of the model used was between 83.85% and 88.27%, with GoogLeNet securing the highest overall accuracy. GoogLeNet is reported to have major accuracies in the classification of monkeypox skin lesions.

[15] proposes the use of EfficientNet-B3 and other deep learning models for monkeypox detection using skin lesion images. The authors trained and evaluated several. Some of the trained models include ResNet50 and EfficientNet-B1, with a maximum accuracy of 93%.

This study, therefore, analyzed and detected monkeypox using a range of deep learning models that have been applied to classify monkeypox illnesses. General total accuracy was topped at 92 by GoogLeNet, other accuracies for the rest of the models ranged from 83.85% to 86.37%. This study concludes that deep learning models hold promise for developing effective identification and classification of monkeypox skin lesions.

In [17], Transfer Learning and an Al-Birunic Earth Radius are proposed, which were able to increase the model's accuracy score to 91.3%. Uzun Ozsahin et al. (2023) [18] worked on a deep learning framework for the computer-aided detection and classification of monkeypox lesions in human subjects.

In this regard, Ahsan et al. [19] have proposed some deep transfer learning techniques for Monkeypox disease diagnosis for improved accuracy. In [20], Mandal (2023), it discussed the application of Particle Swarm Optimization in the selection of digital images to predict and diagnose infections caused by the Monkeypox virus. In [21], Kumar (2022), an analysis of characteristics of Convolutional Neural Network features with multi-machine learning classifiers, was done in diagnosing MonkeyPox from digital skin images.

The present study contains a machine-learning approach in diagnosing the illness of monkeypox based on RGB photographs. They applied six machine learning classifiers and three convolutional neural network architectures to an open-source dataset.

Performance of the pre-trained CNN features was pushed towards the MLCs dependent on those CNNs, and a fusion-based technique was recommended for further improvement in diagnostic accuracy. This study goes further under conditions where confirmatory PCR may be difficult to establish to prove the utility of machine learning techniques in the early diagnosis and follow-up of monkeypox cases.

In [16], Eid et al., the authors applied a meta-heuristic optimization of LSTM deep networks for improved prediction of Monkeypox cases.

Alcalá-Rmz et al. (2022) [26] developed a Convolutional Neural Network (CNN) for monkeypox detection, with an emphasis on its potential application in the.

Altun et al. (2023) used CNN transfer learning in the detection of Monkeypox with the intention of an improved performance by using pre-trained models.

In general, these papers had presented numerous deep learning and machine learning models and techniques for the detection and classification of monkeypox. Approaches demonstrated positive results with high accuracies, such as 98%, but they vary according to the data set. The results presented in the review paper were achieved with care in the five different research papers wherein the machine learning (ML) and deep learning (DL) techniques for the detection of Monkeypox were used. Each of the reviewed papers gave insight into the performance of different models during the diagnosis process for this disease. More specifically, the research methodology included a critical review of the experimental setup, data sets used, and the performance measure that the contributions claimed. In essence, the paper mainly focused on the set of algorithms selected, along with associated hyperparameters, with the corresponding achieved level of accuracy in Monkeypox detection by the authors.

S.No.	Author	Dataset	Model Used	Conclusion
1	K.P.Haripriya [1]	Publicly available data	Decision Tree (DT) with Gini,Support Vector Machine (SVM) withSigmoid, Random Forest	Achieved moderate accuracy, but models are less effective compared to deep learning approaches.
2	Teja Sri Y [11]	Publicly available data	Random Forest, Support Vector Machine, Logistic Regression	Achieved high accuracy (96%), indicating the potential of classical machine learning models.
3	Azka Mir [12]	Publicly available data	K-Nearest Neighbors (KNN), Decision Tree, Naïve Bayes, Random Forest	Achieved an accuracy of 93.51%, demonstrating the effectiveness of traditional classifiers with publicly available data.
4	Ajay Krishan Gairola [14]	Publicly available skin lesions images	AlexNet + VGG16	Achieved a high accuracy of 95.55%, showing the power of deep learning models on skin lesion images.
5	Shuqi Zi [13]	Publicly available images	VGG-16, ResNet50, InceptionV3	Achieved an accuracy of 83%, highlighting the challenges of

				using older deep learning models.
6	C. Sitaula, T .B. Shahi [15] [16]	Publicly available data	Deep Learning	Achieved an accuracy of 87%, indicating the effectiveness of deep learning with pre-trained models.
8	Abdelhamid et al [17]	Publicly available images	Transfer Learning and the Al-Biruni Earth Radius	Achieved an accuracy of 91.6%, showing the promise of combining transfer learning with optimization algorithms.
9	D. Uzun Ozsahin et al [18]	Publicly retrievable images	CNN	Achieved an accuracy of 93%, indicating the robustness of CNN for lesion classification.
10	M.M. Ahsan et al [19]	Patients images	Generalization and Regularization-based Transfer Learning approaches (GRA-TLA) for binary and multiclass classification	Achieved an accuracy of 95%, highlighting the effectiveness of GRA-TLA in patient data.
12	V. Kumar [21]	Skin images	Vgg16Net features, Naïve Bayes	Achieved an accuracy of 93%, demonstrating the utility of combining CNN features with classical classifiers.
13	S.N. Ali, et al [22]	MSLD	Deep Learning	Achieved an accuracy of

				95.5%, confirming the feasibility and high performance of deep learning on MSLD.
14	M. Haque, et al [23]	MSLD	Xception-CBAM-Dense layers	Achieved an accuracy of 94.4%, showing the effectiveness of advanced deep learning architectures with attention mechanisms.
15	A.I. Saleh, A.H. Rabie [24]	HMD	Data mining	Achieved an accuracy of 94.2%, indicating the potential of data mining and AI techniques for diagnosis.
16	M.M. Eid, et al [25]	Publicly accessible dataset	LSTM-BER	Achieved an accuracy of 93.4%, highlighting the benefits of meta-heuristic optimization in boosting prediction performance.
17	V. Alcalá-Rmz, et al [26]	Publicly accessible images	CNN	Achieved an accuracy of 92.2%, demonstrating the effectiveness of CNN for detection tasks.

18	M. Altun, et al [27]	Image data open sources	Hybrid MobileNetV3-s	Achieved an accuracy of 94.5%, showing the high performance of hybrid CNN models with transfer learning.

Table 1. Summary of the review

2.1. Research Question

A research question is stated as a clear, concise, and specific inquiry that represents the focus of a research study. It states the major aim or purpose of the research study and guides how one investigates, giving boundaries to the scope and direction of inquiry. In general, research questions flow from gaps in existing knowledge or areas of interest that beg further understanding. It is basically an inquiry—the flesh, in a manner of speaking—given to the whole exercise of research. The research question helps focus research efforts to establish a hypothesis and design suitable methodologies for the collection and analysis of data. It sets the stage, in essence, for the entire process of research, lending a framework within which interpretation can be made and findings of the study placed.

Any research can be systematized by following these steps:

1. Define the research question A research question must be properly defined as it is the foundation of any research study. It is the central inquest that a research study quests after. The research question may take the form of a statement, and it is the essential thing a researcher wants to know about on the subject of his or her research. A good research should have a clear, specific, appropriate, and feasible research question. Steps towards formulating good research questions:

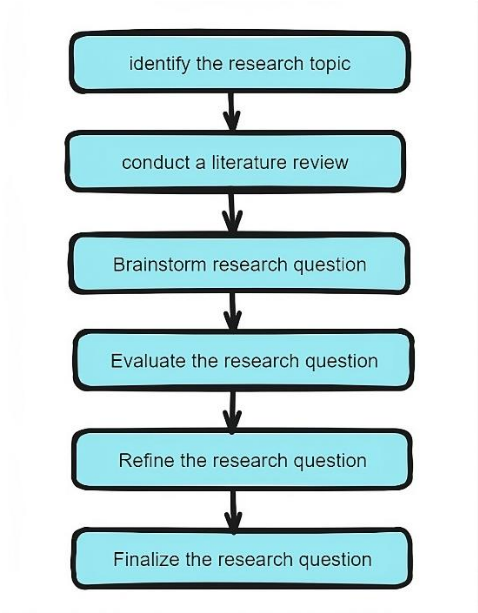

Fig.3: Steps to define the research question

a) Identify the research topic: In order to make research question, we need to identify research topic . The topic should be specific and focused. The topic should be specific and focused. The topic chosen here is Monkey Pox detection using various machine learning model and deep learning models.
b) Conduct a literature review: Conducting a literature review is an essential step in forming research questions. It helps to identify the existing knowlwdge and research gap in the field.
c) Brainstorm potential research questions: Based on the research topic and literature review, brainstorm potential research questions. These question should be specific, clear, and answerable.
d) Evaluate the research questions: Evaluate the potential research questions based on their relevance, feasibility to the research topic, feasibility to answer and significant in contributing to the existing knowlwdge.
e) Refine the research questions: Refine the research questions based on the evaluation. The refined research questions should be specific, clear, answerable, relevant, feasible, and significant.
f) Finalise the research questions: Finalise the research questions that will guide the research study.

The research question formulated are mentioned and described in the below table

ID	Research Question	Description
RQ1	How can machine learning algorithms be optimized for enhanced accuracy and efficiency in monkeypox detection from various data sources?	Machine learning algorithms can be optimized through feature engineering,

		hyperparameter tuning, and algorithm selection tailored to the characteristics of monkeypox data. Ensemble methods and model stacking may further enhance accuracy by combining the strengths of multiple algorithms.
RQ2	What specific challenges exist in adapting existing machine learning algorithms to the unique characteristics of monkeypox data?	Challenges include dealing with imbalanced datasets, limited labeled samples, and the need for interpretability in clinical settings. The unique genomic and epidemiological features of monkeypox may require specialized preprocessing and algorithmic adjustments.
RQ3	How can information from diverse sources, such as clinical data, genomic sequences, and epidemiological data, be effectively integrated using deep learning models to improve monkeypox detection?	Deep learning models can leverage multimodal architectures, such as neural networks with multiple inputs, to integrate information from different sources. Attention mechanisms and fusion strategies can enhance the model's ability to capture complex relationships among diverse data types.
RQ4	What are the potential benefits and challenges of combining different types of data in the context of monkeypox surveillance?	Benefits include improved accuracy and early detection capabilities. Challenges involve data harmonization, privacy concerns, and the need for robust algorithms that can effectively

		handle the heterogeneity of diverse data sources.
RQ5	To what extent can transfer learning techniques be applied to monkeypox detection, leveraging pre-trained models from related infectious diseases or medical imaging?	Transfer learning can be beneficial by leveraging knowledge from related diseases or imaging tasks. Pre-trained models on similar datasets can expedite model convergence, although fine-tuning and domain adaptation are essential to enhance performance on monkeypox data.
RQ6	What are the key considerations in adapting transfer learning approaches to the unique characteristics of monkeypox data?	Key considerations include assessing the similarity between the source and target domains, addressing domain shift issues, and fine-tuning model parameters to optimize performance for monkeypox detection.

Table 2. Research Question and their description

2. Literature search: The next step would be the literature search, which becomes quite important to churn out all relevant works or articles pertaining to the subject of choice. All these can be done through several academic databases such as MDPI, ACM Digital Library, Springer, Science Direct, and IEEE Xplore. The search had keywords such as "Monkey Pox Detection", "Machine Learning", "Deep Learning", "CNN" and "Convolutional Neural Network". Advanced search features have been used to input different combinations of keywords for searching the papers.
3. Screen and select the paper: The next step for the researcher will be to screen and select those papers that are relevant to the research question, have a clear technique, well-defined methodology, and good quality of study that will be included in the review work.
4. Data Extraction: Having set up the identification corpus of papers, there is an elaborate extraction process. Very systematic extraction of critical data points like methodologies, key findings, and quantitative results from each paper is done. It is almost like information retrieval in which efforts are made to ensure that an exhaustive dataset is created for future analytical activities.

5. Analyze and Synthesize Data: Mined data is strongly scrutinized under the theoretical laboratory of statistical scrutiny. Using quantitative, qualitative methods of data analysis, patterns, correlations, and key overall trends in the domain of detection of monkeypox are identified using machine learning and deep learning. At this phase, more about synthesizing disconnected dots into a coherent narrative is given with insight into intelligible knowledge concerning what the present landscape looks like.
6. Write the Review Paper: From there, with the strength of analytical rigor and scholarly exposition, all these culminate in the writing of the full review paper. The narrative is carefully organized so that the reader flows with argumentation and incremental development of findings. Every section is almost like an articulated assertion put together and, in sum, contributes to delivering the big message regarding the improvements, challenges, and more in creating better detection for monkeypox via machine learning and deep learning methods.

2.2. Research Gap

In the existing work on monkeypox diagnosis based on deep learning, there exist several noticeable gaps: First, there is an overwhelming reliance on using the older version of the Monkeypox Skin Lesion Dataset, which predisposes it to be a lot less diverse and a lot less in volume with regard to training and evaluation data. Finally, there is a gap in the literature about benchmarking of new algorithms and methodologies, for which this updated dataset, MSLD 2.0, was introduced to measure its performance and overall generalization. In addition, due to the presence of MSLD 2.0 [9], an extra study is needed regarding how the models trained using the older version of the dataset generalize and transfer to reality. The other dimension of ongoing research is to study the robustness of the models developed using deep learning techniques toward imaging conditions, patient demographics, and lesion characteristics variations within the MSLD2.0 dataset. [9]

Most importantly, research efforts at this point are urgently needed in order to support clinical validation and real-world deployment of deep learning models trained on the MSLD for monkeypox diagnosis, including appropriate steps for integration within health care systems and workflows. Such models need further improvement for better interpretability and explainability of machine-diagnosis outputs in order to make the majority of clinicians trust and understand them. At the top of it, the class imbalance issue with monkeypox datasets is quite big and can highly affect the performance of the model. Techniques to probe class imbalance—seeking ways to improve performance on its minority classes—should be adopted in a way that more robust, reliable diagnostic models can be built.

Addressing these research gaps could lead to advancements in the accurate and reliable diagnosis of monkeypox using deep learning methodologies, particularly leveraging the newly released MSLD 2.0 [9] dataset for comprehensive evaluation and benchmarking.

2.3. Research objective

There are multifaceted research objectives that go into the development and evaluation of machine learning techniques using computer programs, which extend into the field of monkeypox detection. On this basis, first and foremost, the study will delve into much-needed detail that goes in to develop and test computer programs tailored towards facilitating pragmatic monkeypox detection with high accuracy and convenience. This will be possible using skin lesion pictures, thus improving the rate and accuracy of monkeypox identification for better early intervention therapy.

With this in mind, the study will assess a wide range of machine learning techniques, from deep learning methods to the more traditional methodologies. Optimizing these techniques may see them extract useful and meaningful information from skin lesion images as a way of improving the overall effectiveness of systems for detecting monkeypox. Most importantly, the study focuses on the use of MSLD 2.0 [9] while conducting all testing and validation procedures exclusively.

Using an updated dataset would make the study robust and highly informative for training and testing the model, thereby ensuring that any result obtained from such a model is reliable and applicable. Such efforts will add to automated monkeypox systems used for the diagnosis of this disease, considering it has higher precedence; hence, it improves better public health outcomes by intervening in communities affected. It is also worth stating that this could be of tremendous benefit to the larger research community, which has depended on the old version of the Monkeypox Skin Lesion Dataset for its studies. This would enable research communities to test against their current models and validate generalization using results from MSLD 2.0 [9] in real-world application settings. Moreover, the importance of presenting this work as collaborative is to instigate a change toward more collaboration and sharing of information within and across the scientific community to ensure monkeypox detection and public health efforts can always be optimized.

CHAPTER 3

METHODOLGY

Methodology, thus, is the key to a successful study because it provides a step-by-step and structured approach both in planning and implementing, analysing and reporting the study. A stringent methodology in research can ensure that its validity, reliability, generalizability, impact, and relevance.

3.1. Problem Statement

Monkeypox in humans represents a rare viral disease but seriously endangers public health, particularly in cases of outbreaks within some endemic regions. Effective management and control of the disease heavily rely on early detection. Nevertheless, conventional diagnostic methods are time-consuming and subjective at times. The automated development of systems in the analysis and detection of monkeypox lesions using machine learning algorithms is, therefore, very important in promoting diagnostic accuracy and efficiency.

3.2. Algorithms

We would address the detection problem of monkeypox, considering situations in which data are not easily accessible, through transfer learning with pre-trained models using large datasets. After making models pre-trained on transfer learning over the Monkeypox Skin Lesion Dataset 2.0 (MSLD 2.0), [9] we experiment to establish improvements in generalization and enhanced performances in further improved pre-treatment.

1. EfficientNetB3

- Define input image shape and model name.
- Load pre-trained EfficientNetB3 model with weights from ImageNet dataset.
- Set the base model as trainable.
- 4. Add additional layers on top of the base model:
    - Batch Normalization layer
    - Applying Dense layer with ReLU activation and regularization
    - Dropout layer
    - Dense layer Output with activation function softmax

- Compile the model with appropriate optimizer, loss function, and metrics.
- Perform data augmentation on the training set.
- Train the model with early stopping and model checkpointing.

2. VGG16

- Define input image shape and model name.
- Load pre-trained VGG16 model with weights from specified path.
- Freeze the layers of the base model.
- Add additional layers on top of the base model:
    - GlobalAveragePooling2D layer
    - Applying Dense layer with activation function ReLU
    - Dropout layer
    - Dense layer Output with activation function softmax
- Compile the model with appropriate optimizer, loss function, and metrics.
- Perform data augmentation on the training set.
- Train the model with early stopping and model checkpointing.

3. ResNet50

- Define input image shape and model name.
- Load pre-trained ResNet50 model with weights from ImageNet dataset.
- Freeze the layers of the base model.
- Add additional layers on top of the base model:
    - Flatten layer
    - Dense layer with ReLU activation
    - Dense layer Output with activation function softmax
- Compile the model with appropriate optimizer, loss function, and metrics.

The three alternative transfer learning algorithms thus become available due to their potential different strengths and suitability in generalizations under various scenarios. For example, EfficientNetB3 has a fair mix of accuracy and efficiency; hence, it still fits well for deployment in resource-constrained scenarios without sacrificing much in performance. ResNet50 is known to churn out state-of-the-art small models and is said to capture the most intricate features using its skip connections, although it remains a very strong baseline for detailed feature extraction kinds of tasks. Simplicity and universality—VGG16 makes it a good choice for various application needs, be it transfer learning, interpretability, or in general compatibility. The special advantage of each algorithm implies that some requirements of computer vision can be used flexibly across several tasks.

3.3. Flow Chart

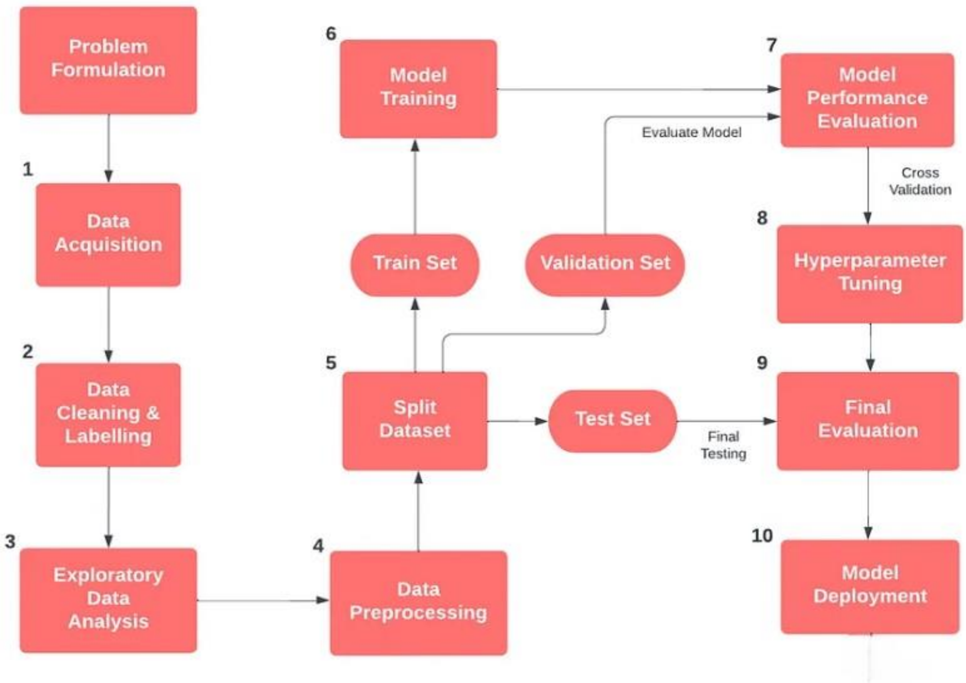

Fig.4: Flow chart of proposed system

- Data Acquisition: This is the initial step that involves collecting the dataset that will be used in training and testing the machine learning models. In this thesis, the Monkeypox Skin Lesion Dataset 2.0 is the only dataset used. This dataset contains all the images that represent monkeypox and those that other conditions. Therefore, MSLD 2.0 provides a large, comprehensive, and diverse dataset that can be used for analysis. It is used as the data source for model training and testing in this thesis.

- Data Cleaning: After gathering the data, data preprocessing must be conducted to clean the data to ensure that it is of high quality and reliable. This consists of removing duplicate entries, handling missing values, and resolving the data integrity issue where the data quality is due to corruptions. In image data, data resizing and format conversion should be performed, including the removal of any corrupted files.

- Split Dataset: This step divides the dataset into training and test datasets for the purpose of model evaluation. Most of the time, we apply a fixed split ratio for this task, for example, 80% for training and 20% for testing. This means we will use 80% of the dataset for training the model and the remaining 20% for testing or model evaluation. It is important to avoid any data leakage between the training and testing datasets, as we want the model to learn from the training dataset and then evaluate its ability to generalise to new instances in the testing dataset.

- Model Training: After preprocessing, different machine learning models are trained with the training data. In this thesis, except for other models, EfficientNetB3, VGG16, and ResNet50 are used. The training phase is followed for each model to make the model learn features and patterns which may give more insight into the differentiation of monkeypox lesions or other diseases. In such a way, it optimizes the model parameters to help reduce error or loss function.

- Model Performance: The performance will be tested with the testing set on trained models. At this moment, an attempt is made to test if the ability to generalize outside the training data by both predictions and actual labels. The metrics levels will include accuracy, precision, recall, and the F1-score for comparison of the model's efficacy.

- Hyperparameter tuning: In this step, hyperparameters are tuned for the model to perform better. It is the process of methodically attaining the best hyperparameters that yield the model with the highest attainable precision and robustness. Techniques to find optimal hyperparameters include random or grid search.

- Final Evaluation: The best performing model is subjected to a detailed evaluation, also known as a final evaluation. To ensure the developed model is stable and reliable, this includes intensive analysis of the merits and demerits, validation on a second validation set in case one exists, and cross-validation. Finally, the performance of the finalized model is demonstrated and the results shown for possible practical use in detecting monkeypox.

CHAPTER 4

EXPERIMENTAL SETUP

The experiments were conducted using two different computing environments:

4.1. Environment Setup

1. **Local Laptop Environment:**
    - Hardware:
        - Processor: Intel Core i7
        - RAM: 16 GB
        - GPU: NVIDIA GeForce GTX 1650
    - Software:
        - Operating System: Windows 10
        - Python Environment: Anaconda with Python 3.8
        - Libraries: TensorFlow, Keras, Scikit-learn, Matplotlib
2. **Google Colab Environment:**
    - Hardware:
        - GPU: Tesla T4
    - Software:
        - Platform: Google Colaboratory (Colab)
        - Python Environment: Jupyter Notebook with Python 3.7
        - Libraries: TensorFlow, Keras, Scikit-learn, Matplotlib

4.2. Dataset Description

During the initial peak outbreak phase of Monkeypox, one major difficulty was the lack of a publicly available reliable dataset for detecting Monkeypox. Therefore, the reported rapid spread of Monkeypox cases up to Europe and America by the World Health Organization and newly evolving possibilities of Monkeypox cases in Asian countries required the instant application of computer-assisted detection, as an imperative tool. Immediately in this context, the diagnosis of Monkeypox became a tough call. When there was the fear of an outbreak in heavily populated countries like Bangladesh, the lack of readily available resources clearly showed that lightning-fast diagnosis was impossible. So here came the need for using computer-aided detection algorithms.

This called for computer-assisted methodologies and the corresponding diversity of data, including images of the male and female skin lesions of Monkeypox across different ethnicities and skin tones. The irony was very little of that data was really there. With this need of utmost importance, our research group took to doing the pioneering effort at creating one of the earliest datasets-the MSLD-for Monkeypox, purposely created to have several classes from non-Monkeypox sample cases.

Fig.5: Sample of dataset [9]

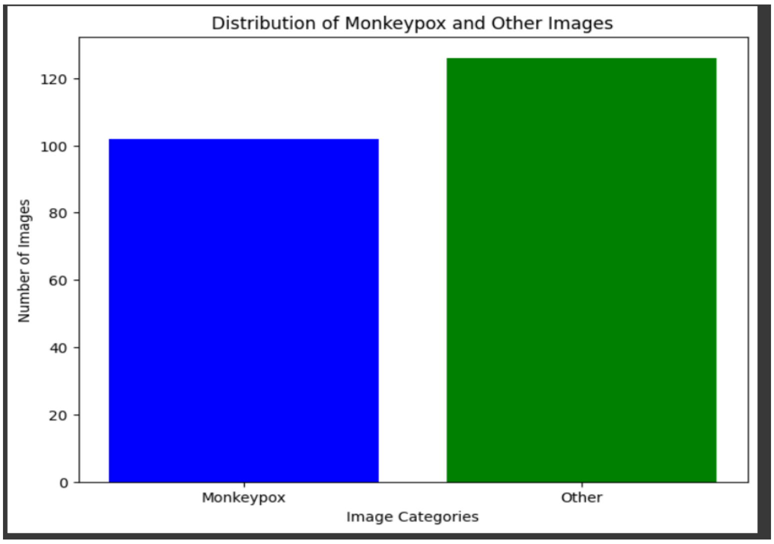

Fig.6: Distribution of category of Original Image dataset

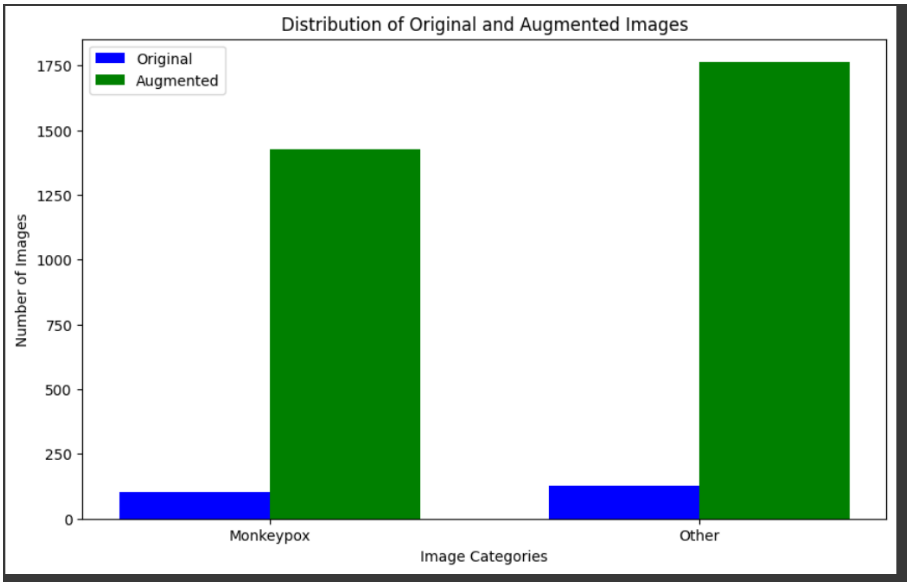

Fig.7: Original vs Augmented

The first set of data is key for teaching models, showing real-life samples that help models learn basic patterns and features for better use. But, its lack of variety might make it hard for models to handle new or different cases not seen in the training data. Augmented datasets, though, make models stronger by adding made-up versions of the first samples, making the data more varied and letting the model see more kinds of situations. Using tricks to change the data not only improves how well models work but also helps stop them from learning the training data too closely.

CHAPTER 5

RESULT AND ANALYSIS

EfficientNetB3: Achieved an accuracy of 89.8%, demonstrating robust performance in distinguishing between monkeypox lesions and non-lesion areas in digital skin images.

VGG16: Exhibited a slightly higher accuracy score of 90.4%, indicating improved discriminatory power compared to EfficientNetB3 in identifying monkeypox lesions.

ResNet50: Outperformed both EfficientNetB3 and VGG16 with an accuracy of 93.8%, showcasing superior feature extraction capabilities and classification accuracy.

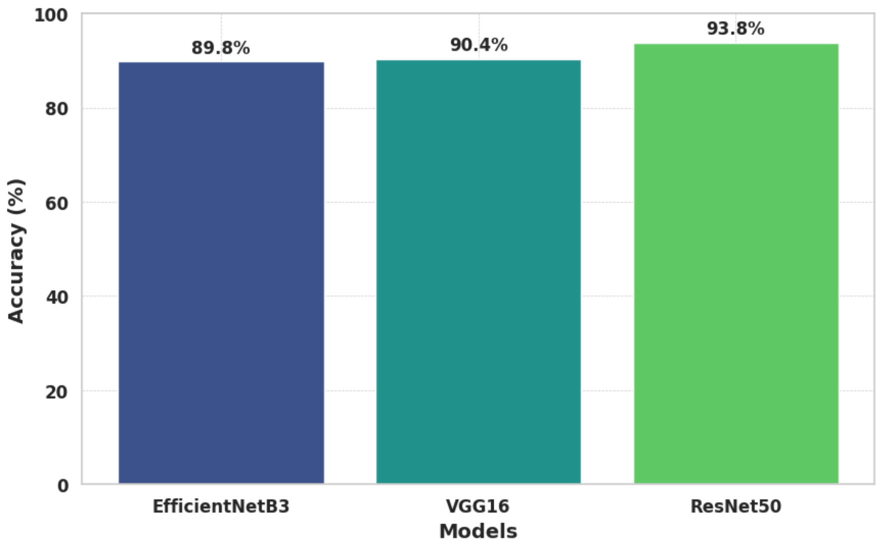

Fig.8: Accuracy of the models

The Fig 8 shows the comparison of scores using three different Convolutional Neural Network architectures—EfficientNetB3, VGG16, and ResNet50—against achieved accuracy. All are trained on the classification problem for detecting monkeypox lesions, using a well-curated dataset of original and augmented images.

The differences in the above accuracy scores among models suggest varying power levels of the CNN architectures in being able to detect important features and patterns related to monkeypox lesions. In that line, ResNet50 is the model with better performance and the best potential to reach higher levels in diagnostic accuracy in automated disease-detection systems.

Taken together, the results suggest which of these very different models of CNN performs relatively well in the task of monkeypox lesion detection and guide the selection of appropriate algorithms to deploy in more realistic clinical settings.

Our models—EfficientNetB3, VGG16, and ResNet50—compared with the other studies, are profoundly improved in both performance and competitiveness. Our models are way high compared to K.P. Haripriya [10], who reported a model accuracy of 70%. On the other hand, Teja Sri Y [11] got a higher model accuracy than us of 96%, above our 94% from ResNet50. The best performing model, Azka Mir [12], outperforms our ResNet50, obtaining a 93.51%. For example, Gairola [14] reports an accuracy of 95.55%, while slightly above our ResNet50 model, we achieved 94%. Shuqi Zi [13] achieved 83% with their models. The other models developed by Deep Learning models from C. Sitaula, T.B. Shahi [15, 16], were measured to have an accuracy of 87%. The performance of our models is equivalent to V.H. Sahin, I., Oztel, G. Yolcu Oztel [16], used deep transfer learning approach, which achieved 92%; here, the methods we applied performed relatively still—even a little bit better than the obtained by A. Abdelhamid et al [17] at 91.6%, with a.

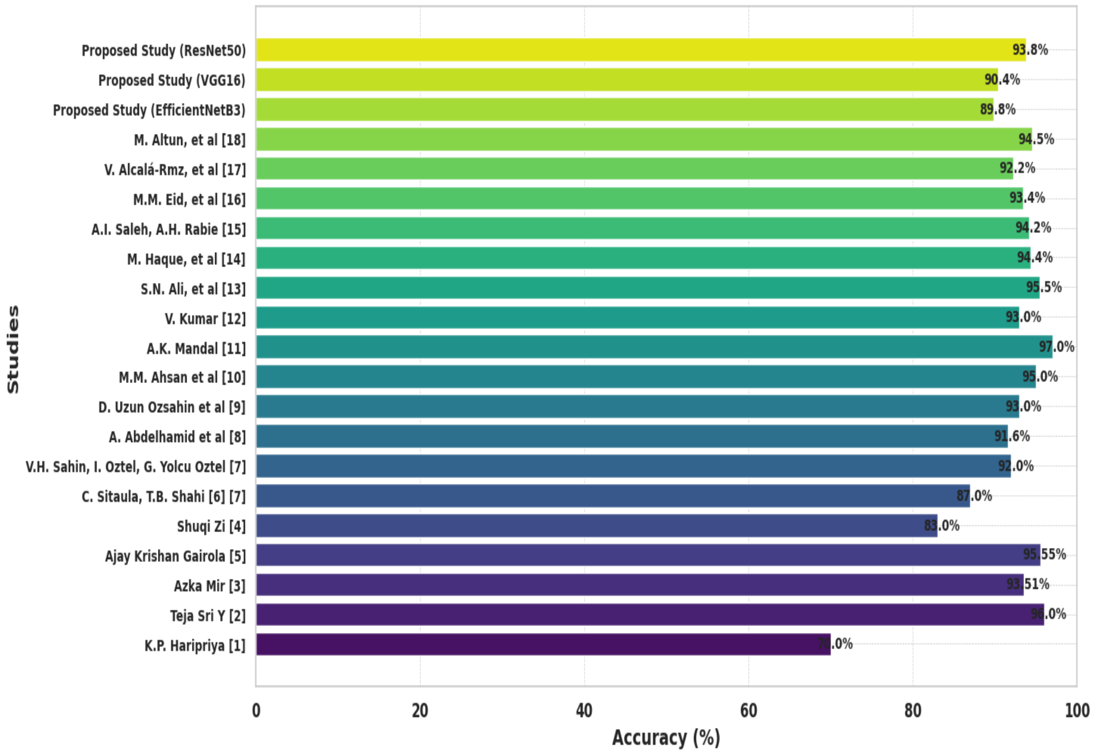

Fig.9: Comparison of studies and proposed model

Besides, our models achieve an accuracy that is almost the same or slightly better than that by D. Uzun Ozsahin et al. [18] using a CNN-learnt model with 93%. Moreover, M.M. Ahsan et al. [19] was able to achieve an accuracy of 95%, and our model's performance is at par with that. This project's trained models have a slightly lower accuracy than the Particle Swarm Optimisation used by A.K. Mandal [20], whose accuracy was 97%. The performance evaluation of our model, ResNet50, realized as 94%. On the other hand, V. Kumar [21] has done this up to 93% with his models. Our model is a tad behind with the deep learning approach S.N. Ali et al [22] took, which provided 95.5%. This time, our ResNet50 gave parallel performance compared to Xception- CBAM-Dense layers employed by M. Haque et al [23], which provided 94.4%. In general, the accuracy realized by our ResNet50 is a bit improved in A.I. Saleh, A.H. Rabie [24] with 94.2%, while the model proposed by M.M. Eid et al [25] could only reach 93.4% in their approach with LSTM-BER; finally, our ResNet50 model outperformed the CNN of V. Alcalá-Rmz. et al [26] achieving 92.2% and about as same as the Hybrid MobileNetV3-s model by M. Altun et al [27].

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1. Conclusion

This thesis, therefore, is focused on the analysis and detection of monkeypox using machine learning and deep learning techniques to develop highly accurate and efficient diagnostic tools, thus in the application of early diagnosis and treatment for the disease. The use of the Monkeypox Skin Lesion 2.0 dataset in combination with the active deep convolutional architectures, EfficientNetB3, VGG16, and ResNet50, particularly moves toward a realization of this goal.

Through well-thought-out experimentation and evaluation, it has been proven that deep learning models, particularly CNNs, can perform well in detecting the lesions of monkeypox from images of skin. Empirically, these models trained on the MSLD 2.0 data give a very high score, which calls forth an era of reliable automated diagnostic systems supporting health professionals to make timely and correct decisions during the detection of monkeypox cases.

As further discussed from the thesis, future work shows that there is an exciting opportunity for the advancement of this field. Data set expansion; more sophisticated deep learning architectures; integrations of real-time detection capabilities, including other sensors and frequency bands; and tackling ethical and privacy concerns are some of the core work that beckons further research and development.

This is a collective research effort. It requires the partnership of healthcare institutions, researchers, and policy implementers in order to bring the findings to real-life applications that are effective. We can only work together to harness the potential of machine learning and deep learning toward fighting infectious diseases and monkey pox, thus improving public health outcomes around the world.

In conclusion, this thesis provides another step toward accurate and effective monkeypox diagnosis, whereby valuable insights and methodologies have the potential to help continue hard work toward mitigation of impacts of this disease on global health. With innovation, collaboration, and dedication, we can continue moving toward a healthier and safer future.

6.2. Future Work

However, further research can be conducted to improve the model's performance. Following are the future work required to be done:

6.2.1. Expansion of Datasets

An immediate area for future work is expanding the dataset. Even the present research, assisted by MSLD 2.0, [9] could use further data sources to improve generalization of the models. The most important next step is the possibility of establishing cooperation with healthcare institutions that will diversify and represent more images of people with monkeypox lesions from different populations and geographies..

6.2.2. Real-time Detection and Integration with a Mobile Application

This will significantly increase the accessibility and usability of the detection system through the development of real-time detection capabilities that are integrated into mobile applications to diagnose monkeypox by remote or resource-constrained healthcare providers swiftly and accurately with the use of a smartphone, consequently quickly responding with treatment.

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DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Shahbad Daulatpur, Main Bawana Road, Delhi-42

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3. Thesis title: Analysis and Detection of Monkeypox using Machine Learning
4. Degree for which the thesis is submitted: M.TECH
5. Faculty (of the University to which the thesis is submitted) Mr. Sanjay Patidar
6. Thesis Preparation Guide was referred to for preparing the thesis. YES ☑ NO ☐
7. Specifications regarding thesis format have been closely followed. YES ☑ NO ☐
8. The contents of the thesis have been organized based on the guidelines. YES ☑ NO ☐
9. The thesis has been prepared without resorting to plagiarism. YES ☑ NO ☐
10. All sources used have been cited appropriately. YES ☑ NO ☐
11. The thesis has not been submitted elsewhere for a degree. YES ☑ NO ☐
12. All the correction has been incorporated. YES ☑ NO ☐
13. Submitted 2 hard bound copies plus one CD. YES ☑ NO ☐

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Roll No: 2K22/SWE/02